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Valuing mortality impacts of smoke exposure from major southern California wildfires

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ABSTRACT

While the mortality impacts of urban air pollution have been well addressed in the literature, very little is known about the mortality impacts and associated social cost from wildfire-smoke exposure (Kochi et al., 2010; U.S. Environmental Protection Agency, 2004). In an attempt to address this knowledge gap, we estimate the social cost associated with excess mortality due to smoke exposure during the 2003 southern California wildfires. Accounting for confounding factors such as seasonality and fluctuation of daily mortality levels, we identify 133 excess cardiorespiratory-related deaths caused by wildfire-smoke exposure. The mean estimated total mortality-related cost associated with the 2003 southern California wildfire event is approximately one billion U.S. dollars. Accounting for mortality costs associated with wildfire-smoke exposure allows for a better understanding of the tradeoffs associated with fuel treatment programs and suppression costs.

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Introduction

Large wildfire events in the United States and around the world have raised concerns about the potential adverse health impacts of exposure to wildfire smoke. However, incorporating the costs associated with health effects, especially mortality effects, of smoke into wildfire-management

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decisions has been hampered by a dearth of quantitative information (Kochi et al., 2010). There have been a few studies that examined the mortality effect of wildfire-smoke exposure. Most of these studies analyzed the 1997 Asian haze event that affected large areas in Southeast Asia between September and November 1997. A mortality effect was observed in areas that experienced extremely high air-pollution levels. For example, Sastry (2002) found a significant mortality effect among the elderly (over 65 years old) following high air pollution days (coarse particulate matter (PM₁₀) over 210 µg/m³) in Malaysia, where the daily average PM₁₀ levels reached as much as 423 µg/m³ and low visibility lasted for 33 days in some areas.¹ Jayachandran (2009) also found a substantial mortality effect from wildfire-smoke exposure among the young (fetuses, infants and children under three years old) in Indonesia, where the hardest hit area recorded daily average PM₁₀ levels of 1000 µg/m³ over several days. The author estimated that wildfire-smoke exposure contributed to over 15,600 premature deaths. Frankenberg et al. (2005) found a significant negative impact on the ability to carry a heavy load, a predictor of later mortality, among people who were exposed to the wildfire smoke in Indonesia. No significant mortality effect was found in areas less affected by wildfire smoke such as Singapore (Emmanuel, 2000) and Thailand (Phonboon et al., 1999).

Although these studies are informative, the 1997 Asian Haze was much larger in scale and longer in duration than the most wildfires in the United States. The exposed population is also quite different from the U.S. population. To our knowledge, there is only one previous study that examined the mortality effect of wildfire-smoke exposure in the United States. Vedal and Dutton (2006) examined mortality levels during the 2002 Hayman fire in Colorado. During the Hayman fire, higher than usual air-pollution levels were observed in the Denver metropolitan area for two separate days.² The authors did not find a significant increase in mortality levels during or following the Hayman fire. This result may be because the increase in air pollution was relatively modest and short lived.

The information gap in the current wildfire literature is problematic for several reasons. First, mortality impacts are often the dominant social cost associated with air pollution (U.S. Environmental Protection Agency, 1999, 2005). Second, catastrophic wildfire events are expected to increase in coming years due to climate change. Finally, information on the mortality costs of wildfire-smoke exposure is needed to help managers understand the benefits of wildfire management actions such as suppression and fuel treatment.

We address this gap in the literature by estimating the mortality cost associated with one of the largest near-urban wildfire events in U.S. history, the 2003 southern California wildfires, which included 14 wildfires that occurred almost simultaneously in late October 2003 (Table 1). The first fire started on October 21st and the last fire was contained on November 4th. The wildfires burned 750,000 acres. Intense smoke from the wildfires affected urban areas in Los Angeles, San Diego, Riverside, Orange and San Bernardino Counties between October 24th and 30th. To estimate the mortality-related cost of smoke exposure from this wildfire event, we first quantify the number of excess deaths associated with wildfire-smoke exposure, then we multiply it by the per unit social cost of premature mortality to obtain the total cost.

In the next section, we describe the analytical methods and data used to quantify the number of excess deaths due to wildfire-smoke exposure. Next, we describe our results. In the third section, we estimate the mortality cost. In the last section, we discuss the conclusions and policy implications.

¹ Particulate matter (PM) is one of the main air pollutants contained in wildfire smoke and the level of PM is often used as a proxy for the intensity of wildfire-smoke exposure (Kochi et al., 2010). Particulate matter (PM) is categorised as PM₁₀, which is particles less than 10 µm in diameter, and PM_{2.5}, which is particles less than 2.5 µm in diameter.

² The high daily average PM_{2.5} levels observed during the Hayman fire were 44 µg/m³ and 48 µg/m³ on June 9th and June 18th, respectively (Vedal and Dutton, 2006). The national daily average PM_{2.5} standard is “the 3-year average of the 98th percentile of 24-hour concentrations at each population-oriented monitor within an area must not exceed 35 µg/m³” (<http://www.epa.gov/air/particlepollution/standards.html>; last accessed on July 15, 2011).

Table 1
2003 southern California wildfires.

	Name	County	Date fire started	Date fire contained	Acres burned	Property damage	Estimated suppression cost
1	Roblar 2	San Diego	10/21	11/4	8592		5,400,000
2	Pass	Riverside	10/21	10/23	2387	5 residences destroyed	1,729,417
3, 4	Grand Prix/Padua	San Bernardino	10/21	11/4	80,340	194 residences, 1 commercial, and 60 other structures destroyed.	12,800,000
5	Piru	Ventura	10/23	11/4	63,991	1 residence, 1 commercial and 6 other structures destroyed.	7,700,000
6	Verdale	LA/Ventura	10/24	10/28	8650	1 other structure destroyed	2,407,000
7	Happy	Santa Barbara	10/24	10/26	250		
8	Old	San Bernardino	10/25	11/4	91,281	940 residence and 30 commercial structures destroyed	37,650,000
9	Cedar	San Diego	10/25	11/4	273,246	2232 residences, 22 commercial and 566 other structures destroyed	29,880,826
10	Simi	Ventura/LA	10/25	11/4	108,204	37 residences, 278 other structures destroyed	10,000,000
11	Paradise	San Diego	10/26	11/4	56,700	221 residences, 2 commercial, and 192 other structures destroyed	13,000,000
12	Mountain	Riverside	10/26	11/2	10,331	21 residences and 40 other structures destroyed.	2,230,000
13	Otay	San Diego	10/26	10/28	45,971	1 residence, 5 other structures destroyed	350,000
14	Wellman	Riverside	10/26	10/27	100		100,000
	Total				750,043	4856 structures destroyed	123,247,243

Source: Appendix 2 in *California Fire Siege 2003: The Story*, prepared by US Forest Service Pacific Southwest Region and California Department of Forestry and Fire Protection.

Quantifying the mortality impact

Analytical methods

There are two possible approaches to quantifying excess mortality from a wildfire event. One is the historical-control method and the other is a regression-model approach. The historical-control method estimates the aggregate impact of an event by comparing total or average mortality levels during a study period (wildfire period) and a reference period (non-wildfire period). With the historical-control method, potential confounding factors are controlled for through selection of appropriate reference periods. Potential confounding factors addressed in the air pollution-mortality literature include seasonality and extreme weather conditions (U.S. Environmental Protection Agency, 2004).

The regression-model approach, usually employed in a time-series analysis framework, allows for estimation of the marginal mortality effect of air pollution associated with wildfire smoke or the wildfire event itself. Confounding variables are included as explanatory variables in the regression model.

The choice of the most appropriate analytical method largely depends on the available data and purpose of the analysis. In this study, we implement a hybrid-approach. We take a regression approach, but we control for confounding factors through selection of appropriate reference periods. We use a difference-in-difference (DID) model to estimate the mortality effects of the 2003 southern California wildfire event using mortality data from the wildfire period (study period) and non-wildfire period (reference period) from 2003, as well as the same periods from control years of 1999–2002^{3,4}:

$$death = \beta_0 + \beta_1 yr2003 + \beta_2 study + \beta_3 yr2003 \times study + \mu \quad (1)$$

where *death* is the number of daily deaths from cardiorespiratory-related causes, *yr2003* is a dummy variable which equals one if the observation is from 2003, and 0 otherwise, *study* is a dummy variable which equals one if the date of death falls during the wildfire period, and 0 otherwise, *yr2003* × *study* is an interaction term between variables *yr2003* and *study* and μ is an i.i.d. error term. The parameter β_3 captures the effect of the wildfire event in 2003 after controlling for the baseline change in mortality risk between the reference and study periods.

To control for seasonal-related confounding factors such as weather conditions, we used a reference period immediately before the wildfire event started. The 2-week reference and study periods were chosen because daily mortality levels between October and November 2003 exhibited a two- to four-day cycle of high mortality (high phase) followed by two to four days of lower mortality (low phase) (see Appendix A). We suspect this is a random fluctuation, but if the wildfire period coincided with the high phase, while the reference period coincided with the low phase, we could mistakenly estimate a positive mortality effect. Since 2-week average mortality levels fluctuate much less, we hope to minimize bias due to the cyclical pattern of mortality levels using 2-week reference and study periods. Specifically, we define October 6–19 as the reference period and October 24–November 6 as the study period.

Previous wildfire-health studies have found that there may be a lagged health effect from smoke exposure. For example, Delfino et al. (2009) examined the morbidity effect of the 2003 southern California wildfires and found that cardiorespiratory-related hospital admissions increased significantly between October 31 and November 15. To capture this effect, we designated a 2 week post-wildfire period 1 (November 7–20), and estimated the following model:

$$death = \delta_0 + \delta_1 yr2003 + \delta_2 post1 + \delta_3 yr2003 \times post1 + \mu \quad (2)$$

where *post1* is a dummy variable that equals one if the death occurred in the post-wildfire period 1, and 0 otherwise. This model was estimated using data from the reference period and post-wildfire period 1 between 1999 through 2003.

Analyzing post-fire mortality also allows us to test for the presence of a harvesting effect, which is a short-term temporal displacement of death (Deschenes and Moretti, 2007). The harvesting effect does not change total mortality; it only shifts the timing of death forward. For example, wildfire-smoke exposure may shorten the lives of people with very frail health. If this is the case, we would expect to see a decline in mortality levels after the sharp increase. Since the sharp increase of mortality levels may appear during the post-wildfire period 1, it is relevant to study the level of mortality after the post-wildfire period 1. We selected one week following the post-wildfire period 1 as the post-wildfire period 2 (November 21–27), and estimated the following model:

$$death = \psi_0 + \psi_1 yr2003 + \psi_2 post2 + \psi_3 yr2003 \times post2 + \mu \quad (3)$$

³ We chose 1999–2002 as control years because there were not any large wildfires linked with diminished air quality during those years for the reference, study and post-wildfire periods (<http://cdfdata.fire.ca.gov/incidents/incidents.statsevents>).

⁴ As described later, this model is estimated separately for each study area.

where *post2* is a dummy variable that equals one if a death occurred in post-wildfire period 2, and 0 otherwise. This model was also estimated with data from the reference period and post-wildfire period 2 between 1999 through 2003.

Since the daily number of deaths is a small nonnegative number, we used a Poisson regression model to estimate Eqs. (1)–(3). However, the Poisson regression model has the restrictive assumption that the variance equals the mean. When this assumption was violated, we estimated a negative binomial regression model that has more flexible distributional assumptions.

Data

We combined data from two sources. Daily mortality data were obtained from the California Department of Health Services, Center for Health Statistics (date of death, zipcode of deceased, cause of death, and age of deceased).⁵ Air pollution data were collected from the California Environmental Protection Agency Air Resources Board and the United States Environmental Protection Agency (U.S. EPA).

We created a daily count of deaths by cause at the zip-code level then we took two approaches to defining the geographic areas likely impacted by smoke. First, we used satellite imagery to create what we call “smoke-affected areas.” Smoke-affected areas are the areas within Los Angeles, Orange, Riverside, San Bernardino, and San Diego Counties and surrounded by the Pacific Ocean, Los Padres National Forest, Angeles National Forest, San Bernardino National Forest and Cleveland National Forest. The wildfires occurred within the urban-interface of these forested areas and smoke drifted toward the Pacific Ocean between October 23rd and 29th, 2003 (see Fig. 1). We also included the area 15 miles around the city of Victorville, as this area also experienced substantial smoke exposure. Satellite images confirm that most of these areas were covered by wildfire smoke. However, since the degree of smoke exposure at ground level cannot be ascertained from satellite images, our definition of smoke-affected areas may be subject to error.

To examine the association between wildfire-smoke exposure at the ground level and mortality levels more accurately, we also created study areas. We define a study area as the area around each of the daily particulate matter (PM) monitoring stations. Daily PM monitoring stations record ground level PM and, therefore, provide a more accurate measure of smoke exposure.

Twelve monitoring stations recorded daily PM levels between October and November 2003 in Los Angeles, Orange, Riverside, San Bernardino and San Diego Counties. We defined a study area as approximately 15 miles around each monitoring station to assure homogeneity of exposure to the recorded PM levels.⁶ We used Geographic Information System (GIS) to obtain the list of zip codes included in each study area, and we aggregated the zip code mortality data into the study areas.⁷ We focused our analysis on the five study areas that showed relatively large numbers of cardiorespiratory deaths and recorded high PM levels during the wildfire period. Fig. 2 shows the location of the five study areas: Los Angeles, North Long Beach, Azusa, Anaheim and San Diego. As shown in Fig. 2, the Anaheim, North Long Beach, Los Angeles and Azusa study areas overlap. To avoid double counting we created three “new” study areas that removed all overlapping areas. The new-North Long Beach (NLB) study area removed the overlapping area with the Anaheim study area. The new-Los Angeles study

⁵ Any analyses, interpretations or conclusions should be attributed to the authors and not to the California Department of Health Services, Center for Health Statistics.

⁶ We compared the daily PM levels of each air monitoring station with the PM levels recorded in all monitoring stations within 20 miles during the wildfire event. Overall, if two monitoring stations are located 15 miles or more from each other, there were noticeable differences in recorded PM levels between two monitoring stations. When the distance is less than or equal to 5 miles, the PM levels of two stations tended to coincide. Between 6 and 15 miles distance, the two PM measures matched well, with few exceptions. Generally it seems reasonable to assume that an area of 15 miles around each daily PM monitoring station was homogeneous with respect to the PM levels.

⁷ Specifically, first we mapped air monitoring stations and zipcode areas in different layers on GIS. We buffered each monitoring station by 15 miles, and we overlaid the buffer layer and zipcode area layer. If the center of zipcode polygon lay within the buffer, then we included this zipcode area in that study area. The zipcode area layer is obtained from <http://www.census.gov/geo/www/cob/z52000.html#shp>. We thank Pam Froemke at U.S. Forest Service, Rocky Mountain Research Station for her assistance with the GIS.



Fig. 1. Satellite image of southern California on October 26, 2003.

Source: NASA's Earth Observatory, <http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=12373>.

area removed the overlapping area with the Anaheim and North Long Beach area. And the new-Azusa study area was created by removing the overlapping areas with the Anaheim, North Long Beach and Los Angeles study areas.

Mortality impact analysis results

Air-pollution levels during the wildfire

Fig. 3 shows the daily average $PM_{2.5}$ level between October 10th and November 10th 2003 in the five study areas. $PM_{2.5}$ levels started to increase on October 24th and exceeded the national daily average standard of $35 \mu\text{g}/\text{m}^3$ for 5 or 6 days.⁸ Wind direction shifted on October 29th, and, by October 30th, $PM_{2.5}$ levels had returned to normal across these areas. Among the five study areas, the San Diego study area experienced the worst air quality during the wildfire. The $PM_{2.5}$ level reached $104 \mu\text{g}/\text{m}^3$ on October 26th and further increased to $170 \mu\text{g}/\text{m}^3$ on October 27th. Although the monitoring data are missing, it is likely that city of San Diego experienced a high $PM_{2.5}$ level on October 28th, as satellite images show heavy smoke covering the city on that day.

The North Long Beach and Anaheim study areas also experienced severe air pollution. The $PM_{2.5}$ levels were over $90 \mu\text{g}/\text{m}^3$ for three days in North Long Beach and reached over $70 \mu\text{g}/\text{m}^3$ for at least two days in Anaheim. Los Angeles and Azusa study areas experienced less severe air pollution compared to the other study areas. Although not shown in Fig. 3, the city of Victorville in San Bernardino County also had intense air pollution on October 29th and 30th, when daily average PM_{10} levels reached to $361 \mu\text{g}/\text{m}^3$ and $227 \mu\text{g}/\text{m}^3$, respectively.

⁸ This reference to the national standard here is approximate. See footnote 2 for the exact definition of national daily average $PM_{2.5}$ standard.

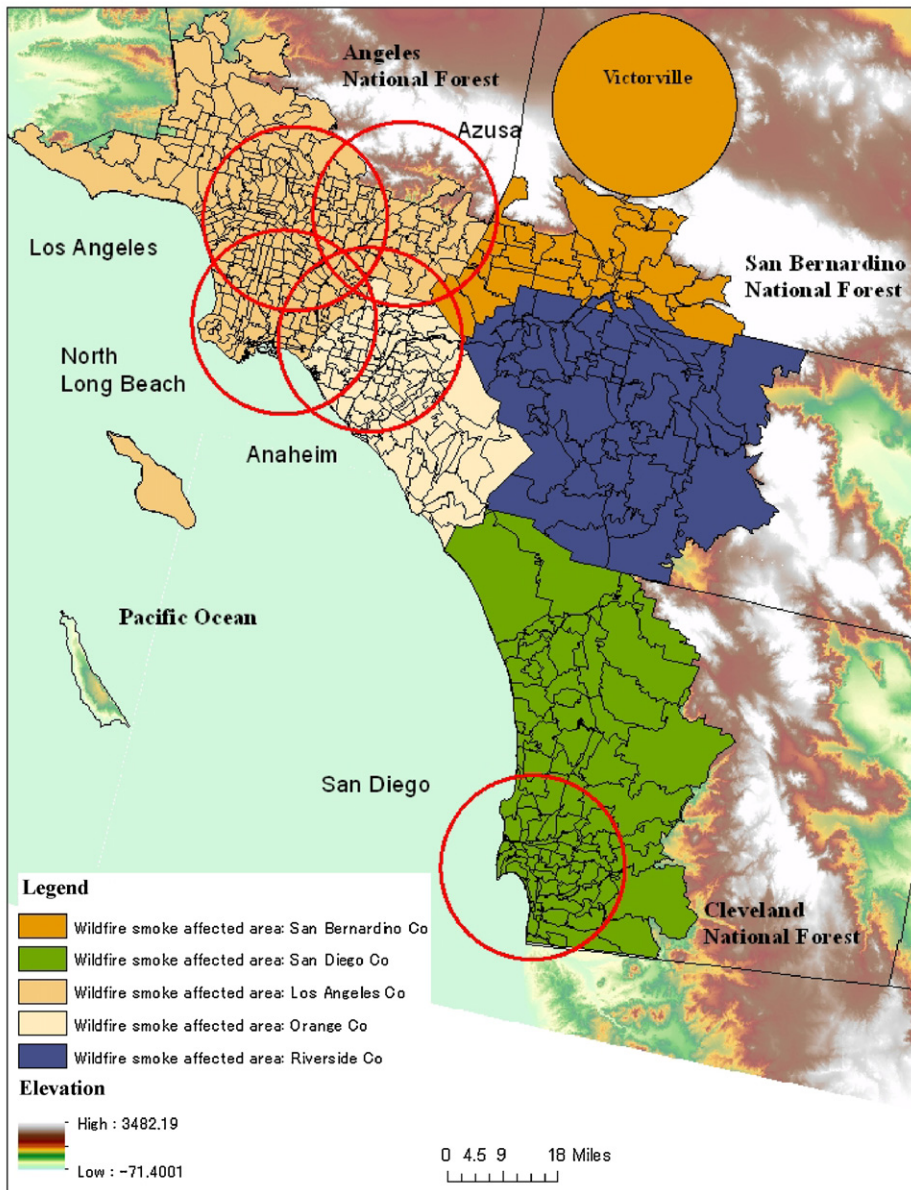


Fig. 2. Map of five study area locations. The 15 miles study area is illustrated with circle.

Daily average mortality levels

Table 2 shows the average daily number of cardiorespiratory-related deaths in each smoke-affected area and study area during the reference, study, and post-wildfire periods in 2003. Table 3 shows the coefficient estimates of the smoke affected and study areas from the DID models based on Eqs. (1)–(3). For succinctness, we only report the coefficient of interaction term for each model. Full model results are reported in the appendix. Based on a goodness-of-fit test using deviance statistics, model (3) for

Table 2

The daily average number of cardiorespiratory-related deaths.

	Reference period (10/6–10/19, 2003)	Study period (10/24–11/6, 2003)	Post-wildfire period 1 (11/7–11/20, 2003)	Post-wildfire period 2 (11/21–11/27, 2003)
<i>Smoke affected area by county</i>				
Los Angeles (LA)	69.57	72.42	76.57	83.85
Orange (OR)	21.92	22.28	26.14	23.85
San Bernardino (SBe)	10.71	13.57	12.28	13.71
San Diego (SD)	23.64	21.35	25.07	25.28
Riverside (RS)	13.28	13.35	13.92	14.42
<i>Study area</i>				
San Diego	12.71	13.42	14.64	13.57
Anaheim	27.57	29.42	35.35	31.57
North Long Beach (NLB)	31.28	34.71	36.85	35.71
New-NLB (excluding Anaheim)	15.78	16.28	15.92	17.71
Los Angeles (LA)	41.92	43.28	46.57	50.14
New-LA (excluding Anaheim and NLB)	27.64	27.28	29.07	32.85
Azusa	17.92	18.78	20.21	23.57

Table 3

Estimated interaction coefficients from 36 separate difference in difference models. Dependent variable for all models is daily number of cardiorespiratory deaths. Standard errors are reported in parenthesis.

	Yr2003 \times study ^a	Yr2003 \times post1 ^a	Yr2003 \times post2 ^b
<i>Smoke affected area by county</i>			
Los Angeles (LA)	0.0147 (0.0499)	0.0511 (0.0493)	0.0797 (0.0649)
Orange (OR)	−0.0197 (0.0902)	0.1022 (0.0873)	−0.0295 (0.1077)
San Bernardino (SBe)	0.2530** (0.1223)	0.1175 (0.1243)	0.2231 (0.1467)
San Diego (SD)	−0.1031 (0.0885)	0.0877 (0.0858)	0.0519 (0.1042)
Riverside (RS)	−0.0663 (0.1157)	−0.0205 (0.1147)	−0.0785 (0.1378)
<i>Study area</i>			
San Diego	0.0289 (0.1157)	0.1500 (0.1140)	0.0191 (0.1493)
Anaheim	0.0116 (0.0788)	0.2103*** (0.0762)	−0.0067 (0.0937)
North Long Beach (NLB)	0.0741 (0.0733)	0.1249* (0.0724)	0.0203 (0.0880)
New-NLB (excluding Anaheim)	0.0416 (0.1048)	−0.0355 (0.1050)	0.0531 (0.1248)
Los Angeles (LA)	−0.0147 (0.0642)	0.0660 (0.0633)	0.0741 (0.0751)
New-LA (excluding Anaheim and NLB)	−0.0636 (0.0799)	0.0027 (0.0789)	0.0858 (0.0931)
Azusa	−0.0204 (0.0980)	0.1005 (0.0968)	0.1730 (0.1306)

^a Estimated using a Poisson model.^b Estimated using a negative binomial model for Los Angeles smoke affected area, San Diego study area and Azusa study area sample and estimated using a Poisson model for all other areas.* Significant at $\alpha = 0.10$ level.** Significant at $\alpha = 0.05$ level.*** Significant at $\alpha = 0.01$ level.

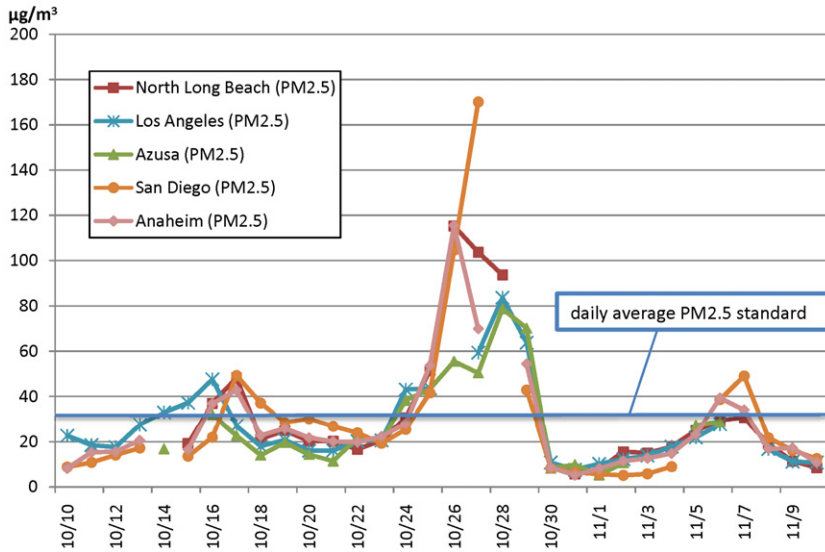


Fig. 3. PM_{2.5} levels in southern California in October–November 2003.

Los Angeles smoke-affected area, San Diego study area, and Azusa study area are found to violate the Poisson distribution assumption at the 10% significance level.⁹ Thus, we re-estimated model (3) for these areas using a negative binomial regression model. The estimated coefficients shown in Table 3 represent the proportional change in cardiorespiratory-related mortality levels after controlling for baseline mortality. We converted the estimated proportional change to the exact percentage changes by using the following formula: $[100 \cdot (\exp(\hat{\beta}) - 1)]$, where $\hat{\beta}$ is the estimated coefficient (Wooldridge, 1999).

After controlling for baseline mortality, we observed significant changes in mortality levels in the San Bernardino county smoke-affected area during the study period, and the Anaheim and North Long Beach study areas during the post-wildfire period 1. The San Bernardino county smoke-affected area showed an increase in daily cardiorespiratory-related mortality level of approximately 25.3%, or exactly by $100 \cdot (\exp(0.2530) - 1) = 28.79\%$ during the study period. Hereafter, we discuss our results using the exact percentage change. The 95% confidence interval of this estimate is between 1.34% and 63.69%. This increase is statistically significant at the 5% level, and is equivalent to a point estimate of 3.08 excess deaths daily or 43.17 total excess deaths (95% confidence interval of 2.00–95.50 total excess deaths). Since the periods following the study period did not show a decline in mortality compared to the reference period, the observed increase in mortality during the study period appears not to be the result of a harvesting effect.

The Anaheim study area showed a 23.40% increase in cardiorespiratory-related deaths during the post-wildfire period 1 with a 95% confidence interval of 6.28–43.29%. The point estimate of daily average number of excess deaths during the post-wildfire period 1 was 6.45 and the total number of excess deaths was 90.32 (95% confidence interval of 24.24–167.09 total excess deaths). There was no significant decline in mortality in post-wildfire period 2 compared to the reference period, which suggests that the observed increase in mortality was not due to a harvesting effect. The North Long Beach study area showed a significant increase in daily mortality in the post-wildfire period 1 relative

⁹ We estimated all models in STATA. A goodness of fit test (estat gof command in STATA) was conducted for each model and if the results suggested rejection of the null hypothesis that the Poisson model is appropriate for the data, we estimated a negative binomial model.

Table 4
Characteristics of deaths during the reference, study and post-wildfire period in the San Bernardino smoke affected area and the Anaheim study area.

San Bernardino smoke affected area	Reference period (10/6–10/19)	Study period (10/24–11/6)	Post-wildfire period 1 (11/7–11/20)
Total number of nonaccidental death	328	362	343
Total number of cardiorespiratory related death	150	190	172
Age > 65	121	150	140
Age ≤ 65	29	40	32
Total number of cardio related death	114	161	135
Total number of respiratory related death	36	29	37
Anaheim study area	Reference period (10/6–10/19)	Study period (10/24–11/6)	Post-wildfire period 1 (11/7–11/20)
Total number of nonaccidental death	760	770	871
Total number of cardiorespiratory related death	386	412	495
Age > 65	319	348	434
Age ≤ 65	67	64	61
Total number of cardio related death	320	334	405
Total number of respiratory related death	66	78	90

to the reference period. However, the increase occurred in the area that overlapped with the Anaheim study area. When we removed the overlapping area, the increase in mortality was no longer observed.

In summary, we observed a point estimate of 133 excess deaths with a 95% confidence interval of between 26 and 262 excess deaths in the San Bernardino smoke-affected area and the Anaheim study area after controlling for the seasonal effect and the natural fluctuation in daily mortality levels. Table 4 provides more detailed characteristics of the excess deaths in these areas. In the San Bernardino smoke-affected area there was a significant increase in cardio-related mortality, whereas respiratory related deaths decreased slightly during the wildfire period. Table 4 also shows the age distribution of the cardio-respiratory deaths. Excess deaths were observed mainly in the over 65 age group but there was also an increase in mortality in the less than 65 age group. In the Anaheim study area, both cardio and respiratory related deaths increased in post-wildfire period 1 relative to the reference period. All of the excess deaths were in the over 65 age group.

Economic cost associated with the excess deaths from the wildfire-smoke exposures

The standard economic approach used to estimate the cost of premature death is the value of a statistical life (VSL). The VSL is a measure of societal willingness to pay to save one anonymous person's life. The total economic cost of premature mortality is obtained by simply multiplying the number of premature deaths attributable to an event by the VSL. The VSL has been estimated through survey and labor market studies where the relationship between additional wage and additional occupational fatal risk are analyzed (Kochi et al., 2006). Previous studies have shown an extensive range of VSL estimates depending on the study design. In our analysis, we use a range of \$1.3–13 million (2008 U.S. dollars). This is the approach used by the U.S. EPA to evaluate the benefits of improved air quality (U.S. EPA, 2005). Using the point estimate of 133 excess deaths, we calculate the mortality cost of the 2003 southern California wildfires to be between \$172.9 million and \$1.729 billion with a mean estimate of \$950.95 million.¹⁰

¹⁰ There has been a discussion that the VSL should be adjusted for the age of the group of people who benefit from the policy. The central issue in this discussion is what the correct VSL for the elderly population group who would be benefited by the air pollution policy the most should be. Since elderly people have fewer remaining years of life than other age groups, they

Conclusions and policy implications

We estimated the mortality impact and economic cost associated with smoke exposure from the wildfires that occurred in southern California in late October 2003. This series of wildfires were some of the largest ever to burn near a major U.S. urban area. The 2003 southern California wildfires burned 750,043 acres, destroyed 3710 homes, and cost \$123 million to suppress. We estimated that an additional 133 people died of cardiorespiratory illness due to wildfire-smoke exposure. Using the VSL employed by the U.S. EPA (2005), the total social cost of these fatalities was between \$172.9 million and \$1.729 billion.

Excess deaths were predominantly among the elderly. We also observed a threshold effect: excess deaths were concentrated in areas with a large exposed population such as Orange and Los Angeles Counties and areas with extremely high air-pollution levels such as the San Bernardino County smoke-affected area (daily PM_{10} level of over $360 \mu\text{g}/\text{m}^3$ and daily $\text{PM}_{2.5}$ level of over $100 \mu\text{g}/\text{m}^3$ in some areas). We did not find significant mortality impacts in less densely populated areas with similar air-pollution levels or in densely populated areas with milder air-pollution levels.

Our results are consistent with Vedal and Dutton (2006), which did not find a significant mortality impact from the Hayman fire that affected a relatively small population (baseline daily cardiorespiratory mortality of approximately 20) and caused much milder increases in daily $\text{PM}_{2.5}$ levels (up to $48 \mu\text{g}/\text{m}^3$). In addition, this threshold effect is consistent with Sastry (2002), which found that the mortality impact from wildfire-smoke exposure was only consistently observed in areas with very high PM levels (PM_{10} level of above $210 \mu\text{g}/\text{m}^3$).

We observed heterogeneity in the timing and cause of mortality (cardio or respiratory). For example, in San Bernardino mortality was relatively immediate and cardio related. In contrast, in Anaheim, mortality was delayed and consisted of both cardio and respiratory deaths. This heterogeneity may be attributed to a number of factors, such as different averting behavior and different demographic characteristics among residents including age, income levels, background health risk and access to medical care. More detailed analysis of this heterogeneous health effect would be useful.

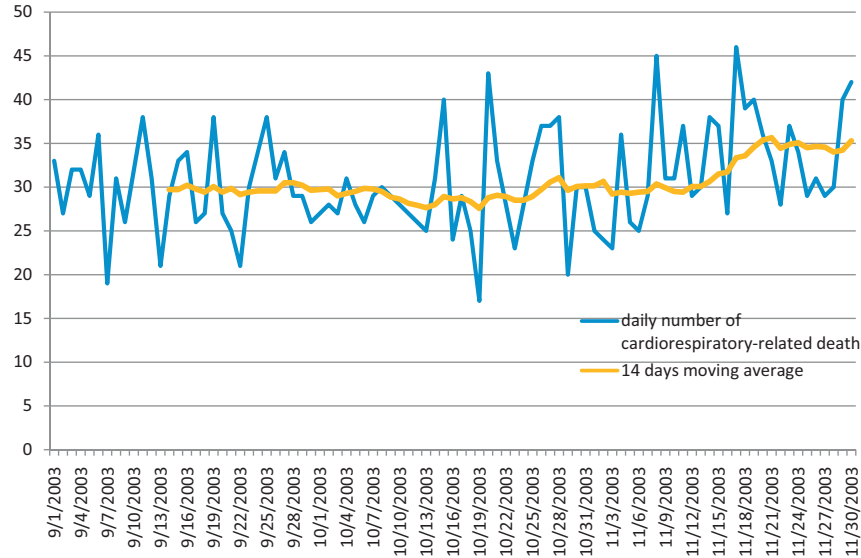
To our knowledge, this is the first study to estimate the mortality impact and associated economic cost of smoke exposure during the 2003 southern California wildfire event. Several studies identified significant morbidity impacts from the 2003 southern California wildfire events such as the increased hospital admission levels (Delfino et al., 2009), emergency department visits levels (Viswanathan et al., 2006; Kene et al., 2008), and adverse health conditions among children (Künzli et al., 2006) suggesting that this mortality study does not capture the full health cost of the 2003 southern California wildfires.

Global climate change is expected to increase the frequency and severity of wildfire events. Areas like southern California may be particularly susceptible to such effects. In fact, southern California has experienced intense fires in 2007 and 2008. Prevention of large wildfires is costly and at times ineffective. However, costly fuel treatments may be justified, if they are found to significantly reduce the health effects associated with wildfire-smoke exposure. Likewise, evacuation of susceptible populations during large wildfire events may also be justified if such actions can reduce health and mortality effects associated with smoke exposure. The bottom line is that full accounting of the social cost of wildfire events should include morbidity and mortality costs.

may be willing to pay less to reduce the mortality risk than younger people. On the other hand, they may be willing to pay more to reduce mortality risk than younger people because the remaining years of life are a scarce good to them. Krupnick (2007) extensively reviewed the existing literature on the relationship between age and VSL. Krupnick concludes that there is no conclusive evidence to discount VSL for an elderly population. Thus we apply the uniform VSL to all age groups.

Appendix A.

Daily number of cardiorespiratory-related death in Anaheim area.



Model 1.^a

	LA affected area	OR affected area	SBe affected area	SD affected area	RS affected area
yr2003	−0.0672* (0.0356)	0.0416 (0.0641)	−0.1044 (0.0904)	−0.0290 (0.0613)	0.0231 (0.0822)
study	0.0256 (0.0218)	0.0359 (0.0408)	−0.0167 (0.0550)	0.0015 (0.0383)	0.0716 (0.0515)
yr2003*study	0.0147 (0.0499)	−0.0197 (0.0902)	0.2530** (0.1223)	−0.1031 (0.0885)	−0.0663 (0.1157)
Constant	4.3096*** (0.0155)	3.0462*** (0.0291)	2.4759*** (0.0387)	3.1921*** (0.0271)	2.5636*** (0.0371)
Pseudo R ²	0.007	0.001	0.006	0.005	0.002
N	140	140	140	140	140
Prob(GOF − Chi2)	0.3725	0.5023	0.6113	0.1436	0.6748

	San Diego study area	Anaheim study area	NLB study area	New NLB study area	LA study area	New LA study area	Azusa study area
yr2003	−0.1215 (0.0828)	−0.0579 (0.0566)	−0.0879* (0.0530)	−0.0887 (0.0746)	−0.0868* (0.0458)	−0.0571 (0.0565)	−0.0609 (0.0702)
study	0.0258 (0.0496)	0.0536 (0.0345)	0.0299 (0.0321)	−0.0104 (0.0456)	0.0465* (0.0276)	0.0506 (0.0345)	0.0671 (0.0426)
yr2003 × study	0.0289 (0.1157)	0.0116 (0.0788)	0.0741 (0.0733)	0.0416 (0.1048)	−0.0147 (0.0642)	−0.0636 (0.0799)	−0.0204 (0.0980)
Constant	2.6642*** (0.0353)	3.3747*** (0.0247)	3.5311*** (0.0229)	2.8478*** (0.0322)	3.8228*** (0.0198)	3.3765*** (0.0247)	2.9473*** (0.0306)
Pseudo R ²	0.005	0.005	0.005	0.002	0.012	0.008	0.006
N	140	140	140	140	140	140	140
Prob(GOF − Chi2)	0.1682	0.1749	0.6786	0.8212	0.3186	0.8588	0.4503

^a All models are estimated through a Poisson regression model.

Model 2.^a

	LA affected area	OR affected area	SBe affected area	SD affected area	RS affected area		
<i>yr03</i>	−0.0672* (0.0356)	0.0416 (0.0641)	−0.1044 (0.0904)	−0.0290 (0.0613)	0.0231 (0.0822)		
<i>Post1</i>	0.0448** (0.0217)	0.0736* (0.0405)	0.0193 (0.0545)	−0.0290 (0.0386)	0.0678 (0.0516)		
<i>yr2003 × post1</i>	0.0511 (0.0493)	0.1022 (0.0873)	0.1175 (0.1243)	0.0877 (0.0858)	−0.0205 (0.1147)		
<i>Constant</i>	4.3096*** (0.0155)	3.0462*** (0.0291)	2.4759*** (0.0387)	3.1921*** (0.0271)	2.5636*** (0.0371)		
<i>Pseudo R²</i>	0.011	0.015	0.002	0.001	0.002		
<i>N</i>	140	140	140	140	140		
<i>Prob(GOF − Chi2)</i>	0.4015	0.5208	0.7910	0.9446	0.5536		
	San Diego study area	Anaheim study area	NLB study area	New NLB study area	LA study area	New LA study area	Azusa study area
<i>yr03</i>	−0.1215 (0.0828)	−0.0579 (0.0566)	−0.0879* (0.0530)	−0.0887 (0.0746)	−0.0868* (0.0458)	−0.0571 (0.0565)	−0.0609 (0.0702)
<i>Post1</i>	−0.0087 (0.0500)	0.0384 (0.0346)	0.0390 (0.0320)	0.0445 (0.0450)	0.0391 (0.0277)	0.0477 (0.0345)	0.0195 (0.0431)
<i>yr2003 × post1</i>	0.1500 (0.1140)	0.2103*** (0.0762)	0.1249* (0.0724)	−0.0355 (0.1050)	0.0660 (0.0633)	0.0027 (0.0789)	0.1005 (0.0968)
<i>Constant</i>	2.6642*** (0.0353)	3.3747*** (0.0247)	3.5311*** (0.0229)	2.8478*** (0.0322)	3.8228*** (0.0198)	3.3765*** (0.0247)	2.9473*** (0.0306)
<i>Pseudo R²</i>	0.003	0.018	0.009	0.006	0.008	0.005	0.002
<i>N</i>	140	140	140	140	140	140	140
<i>Prob(GOF − Chi2)</i>	0.8821	0.2178	0.5419	0.6159	0.1620	0.7311	0.1234

^a All models are estimated through a Poisson regression model.

Model 3.

	LA affected area		OR affected area	SBe affected area		SD affected area	RS affected area		
	Poisson	Negative binominal	Poisson	Poisson		Poisson		Poisson	
<i>yr03</i>	−0.0672* (0.0356)	−0.0672* (0.0392)	0.0416 (0.0641)	−0.1043 (0.0904)		−0.0290 (0.0613)	0.0231 (0.0822)		
<i>Post2</i>	0.1071*** (0.0259)	0.1071*** (0.0289)	0.1138** (0.0486)	0.0237 (0.0666)		0.0153 (0.0467)	0.1610*** (0.0610)		
<i>yr2003 × post2</i>	0.0797 (0.0583)	0.0797 (0.0649)	−0.0295 (0.1077)	0.2231 (0.1467)		0.0519 (0.1042)	−0.0785 (0.1378)		
<i>Constant</i>	4.3096*** (0.0155)	4.3096*** (0.0171)	3.0462*** (0.0291)	2.4759*** (0.0387)		3.1921*** (0.0271)	2.5636*** (0.0371)		
<i>Pseudo R²</i>	0.038	0.028	0.01	0.006		0.001	0.012		
<i>N</i>	105	105	105	105		105	105		
<i>Prob(GOF − Chi2)</i>	0.0389		0.1560	0.5239		0.2253	0.5357		
	San Diego study area		Anaheim study area	NLB study area	New NLB study area	LA study area	New LA study area	Azusa study area	
	Poisson	Negative binominal	Poisson	Poisson	Poisson	Poisson	Poisson	Negative binominal	
<i>yr03</i>	−0.1215 (0.0828)	−0.1215 (0.0878)	−0.0579 (0.0566)	−0.0879* (0.0530)	−0.0887 (0.0746)	−0.0868* (0.0458)	−0.0571 (0.0565)	−0.0609 (0.0702)	−0.0609 (0.0799)
<i>Post2</i>	0.0462 (0.0602)	0.0462 (0.0642)	0.1422*** (0.0409)	0.1121*** (0.0382)	0.0622 (0.0546)	0.1048*** (0.0331)	0.0870** (0.0416)	0.1007** (0.0513)	0.1007* (0.0592)
<i>yr2003 × post2</i>	0.0191 (0.1406)	0.0191 (0.1493)	−0.0067 (0.0937)	0.0203 (0.0880)	0.0531 (0.1248)	0.0741 (0.0751)	0.0858 (0.0931)	0.1730 (0.1126)	0.1730 (0.1306)
<i>Constant</i>	2.6642*** (0.0353)	2.6642*** (0.0376)	3.3747*** (0.0247)	3.5311*** (0.0229)	2.8478*** (0.0322)	3.8228*** (0.0198)	3.3765*** (0.0247)	2.9473*** (0.0306)	2.9473*** (0.0351)
<i>Pseudo R²</i>	0.0065	0.0057	0.0245	0.022	0.006	0.027	0.013	0.017	0.012
<i>N</i>	105	105	105	105	105	105	105	105	105
<i>Prob(GOF − Chi2)</i>	0.0701		0.5129	0.6271	0.8535	0.2380	0.3074	0.0051	

DID estimation results. Standard errors in parentheses; *significant at $\alpha = 0.10$ level; **significant at $\alpha = 0.05$ level; ***significant at $\alpha = 0.01$ level. *Prob(GOF – Chi2)* is the probability of observing given results when the assumption of Poisson distributed data is true. If *Prob(GOF – Chi2)* is less than 0.1, the Poisson regression model is not appropriate and the negative binominal model should be used.

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